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Heterogeneity in some relationships between social media use and emerging adults' affective wellbeing

Nastasia Griffioen[1] · Hanneke Scholten[2] · Anna Lichtwarck-Aschoff[3] · Dominique Maciejewski[1] · Isabela Granic[4]

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Abstract
Group-level studies of the association between social media use and wellbeing in emerging adults have so far yielded mixed and inconsistent results. As a result, recent research has shifted focus towards assessing potential heterogeneity in social media use relationships in youth. In this preregistered study, we aimed to take previous efforts further by incorporating both subjective and objective data, and by including more specific measures of social media use such as how active emerging adults were on social media, and with whom they interacted. While data resolution issues interfered with some of our analyses, our findings suggest that there is heterogeneity in some but not all of the relationships between social media use and emerging adults' affective wellbeing.

Keywords Social media · Heterogeneity · Multilevel models · Affective wellbeing · Positive affect

Introduction

The impact of young people's social media use on affective wellbeing continues to be at the centre of public and scientific debates. Social media continue to play a vital role in many emerging adults' lives, and take up a considerable amount of their everyday leisure time. Even though significant worries continue to exist regarding the effects of social media on youth wellbeing, the many empirical studies that have been conducted in recent years generally show mixed and small group-level effects of social media use on adolescents' wellbeing (Orben et al., 2019; Verduyn et al., 2017). Group-level analyses do not seem to shed much light on the inconsistencies in the literature, because these largely neglect the variations between individuals in the relation between social media use and affective wellbeing. Indeed, recent between-person comparisons have suggested that heterogeneity may exist and may explain the mixed group-level findings (Beyens et al., 2020). Although relatively little is still known about the potential reasons underlying such patterns, novel studies using intensive longitudinal data and state-of-the-art multilevel analyses provide promising avenues for examining social media's effects on affective wellbeing. In the current study, we aimed to contribute to this new area by leveraging these tools and investigating the role of social media use characteristics as well as individuals' psychological characteristics in explaining heterogeneity in wellbeing and social media use relationships.

Specific elements of the social media use experience

Rather than only considering whether and how long social media are used, diving deeper into the specifics of social media use may help differentiate between adverse and beneficial effects. The large body of social media research has shown that young adults' social media use consists of a large and varied ecosystem of apps (Zhao et al., 2016). However, most research has focused on Facebook or Instagram solely. An earlier study has found that there is indeed great variation in the platforms used by emerging adults (Griffioen et al.,

✉ Nastasia Griffioen
nastasia.griffioen@ru.nl

1 Developmental Psychopathology, Behavioural Science Institute, Radboud University Nijmegen, Nijmegen, The Netherlands

2 Faculty of Behavioural, Management and Social Sciences, University of Twente, Enschede, The Netherlands

3 Faculty of Behavioural and Social Sciences, University of Groningen, Groningen, The Netherlands

4 Faculty of Social Sciences, McMaster University, Hamilton, Ontario, Canada

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2021), and that not every young adult uses Facebook and/or Instagram (anymore). In our study, we focus on social media platforms that match the definition given by Bayer and colleagues. These are platforms that are Internet-based, that support asynchronous communication, are user-generated and perceived as social in nature, as well as allow users to broadcast to large audiences (Bayer et al., 2020). We therefore focus mainly on Facebook, Instagram, Twitter, TikTok, and Snapchat. Other platforms that appear in our data will be also taken into account, so as to not exclude them entirely, but will be combined into an 'Other' category.

Different platforms present different affordances by virtue of their design (Moreno & Uhls, 2019; Prinstein et al., 2020). While social media such as Reddit and Facebook are designed to accommodate more verbal interactions, other platforms such as Instagram and Snapchat are built primarily for visual consumption and interactions. Therefore, considering which social medium is used the most when examining momentary affective wellbeing effects could provide a preliminary sense of the types of environments and experiences that are beneficial or detrimental.

Furthermore, social media apps likely produce different experiences as a result of their features. For instance, social media apps' action possibilities can facilitate passive (i.e., scrolling) or active use (i.e., engaging with content) to varying degrees. These distinctions in type of activity while on social media have been investigated extensively in previous group-level studies (e.g., Escobar-Viera et al., 2018; Shaw et al., 2015; Verduyn et al., 2015). Findings suggest that passive use of social media is related to more negative wellbeing outcomes. However, recent work by Valkenburg and colleagues (2021) suggests that the adverse effect of passive social media use may not hold for everyone, and that this association only holds for 20 percent of adolescents.

Last, research suggests that social media apps may differ in the kinds of social contacts they represent to young adults (Vitak & Kim, 2014). Positive interactions on social media seem to stem primarily from close social ties, such as family, friends and romantic partners (Bayer et al., 2016), and being in touch with close social ties has been shown to be related to better mental health outcomes (Rae & Lonborg, 2015). Conversely, contact with more distant social ties (i.e., acquaintances, companies, and even celebrities such as influencers) may elicit other types of emotions, such as annoyance or envy (Singh & Ang, 2020), and may give rise to negative experiences such as social comparison (Vogel et al., 2014, 2015). Furthermore, although the name 'social media' implies coming into contact with people, we have found in earlier work that this is not always the case. Conversations with participants in earlier studies have shown that considerable amounts of content on participants' social media feed stem from companies and their advertisements (Griffioen et al., 2021), fed to users by social media algorithms. Users of social media may find advertisements intrusive and interruptive of their flow (Rettie, 2001; Zhang & Mao, 2016), negatively affecting users' emotional wellbeing. Delving deeper into whom emerging adults interact with and see posts from may help us understand positive or negative effects of social media use.

Psychological characteristics

It is likely that other factors beyond social media use specifics can shed light on potential heterogeneity in the association between social media and affective wellbeing. While external, environmental factors may contribute more to cognitive aspects of wellbeing, personal factors have been shown to relate more to the affective component of wellbeing (Schimmack et al., 2008). A number of studies have explored whether psychological characteristics (e.g., self-esteem, personality) are related to social media use effects at a group-level (e.g., Grace et al., 2015; Wilson et al., 2010), but recent studies indicate that there are interindividual differences in young adolescents when it comes to social media effects (Beyens et al., 2020; Valkenburg et al., 2021). Personal psychological characteristics such as young adults' (a) fear of missing out, (b) sensitivity to rejection, and (c) self-compassion may provide more insight into what may underlie heterogeneity in social media's effects on affective wellbeing.

Fear of missing out (or FoMO for short) is defined as the fear that others are having fun and experiencing exciting things without you (Przybylski et al., 2013). FoMO is thought to be particularly strong when it comes to social media use because users are continuously presented with (often idealized) information about others' activities and experiences. On a group-level, a number of studies have already found that higher levels of FoMO appear to be related to more negative outcomes of social media use, such as social media fatigue and maladjustment to college (Alt, 2016; Dhir et al., 2018). However, it is not clear whether this relationship holds for everyone, and whether variations in FoMO can explain why social media use may be detrimental for some but not for others.

In contrast to FoMO, rejection sensitivity is less frequently examined in relation to social media use. Nevertheless, rejection sensitivity has started to receive some limited attention in the social media and adolescent wellbeing literature. Rejection sensitivity, which is defined as the extent to which one fears and anticipates rejection of the self by others (Downey & Feldman, 1996), is considered an important risk factor for the development of depressive symptoms (Chango et al., 2012). It is possible that rejection sensitivity may play a restraining role on young adults' social media use, keeping them from actively engaging on those platforms out of fear of negative reactions. Young people who are sensitive to rejection may spend their social media time predominantly passively, decreasing their risk of detrimental effects. Empirically, there are already some indications that rejection sensitivity may indeed moderate social media use effects on wellbeing. Rejection sensitivity has for instance been shown to be a predictor of excessive social media use (Demircioğlu & Göncü Köse, 2018). Furthermore, a recent study has shown that individuals sensitive to rejection are less inclined to engage in political conversations on social media (Bäck et al., 2019), most likely out of fear of disagreements and being shunned.

While the majority of dispositional research on social media's effects on wellbeing have focused on risk factors such as FoMO and rejection sensitivity (Burke et al., 2020; Chow & Wan, 2017), relatively little attention has been paid to protective factors, one of which is self-compassion. Self-compassion is defined as "seeing one's own experience in light of the common human experience, acknowledging that suffering, failure, and inadequacies are part of the human condition, and that all people—oneself included—are worthy of compassion" (Barnard & Curry, 2011; Neff, 2003; Reyes, 2012). Although self-compassion is not a novel concept, it has not extensively been studied in relation to social media use. Self-compassion, however, seems important to consider when thinking about the negative effects social media might have on young people's self-image and wellbeing. For instance, higher levels of self-compassion may protect against potential negative effects of social media use: compassion for the (imperfect) self may prevent individuals from experiencing negative emotions as a result of social comparisons online, as suggested by recent studies in the body image literature (Daye et al., 2014; Kelly et al., 2014; Mosewich et al., 2011). In fact, users of social media themselves seem to have realized and started to embrace this. A study by Slater and colleagues has shown that messages of self-compassion shared on social media indeed can mitigate negative effects on users' wellbeing (Slater et al., 2017).

Current study

Determining individual psychological characteristics and their interactions with social media use specifics such as activity and close-tie-interactions will help explain negative versus positive effects on affective wellbeing. In line with past research that used ecological momentary assessments, we operationalize affective wellbeing as positive affect (Beyens et al., 2020; Kross et al., 2013; Valkenburg et al., 2021).

While many previous studies have focused on one particular social network (e.g., Deters & Mehl, 2013; Faelens et al., 2019; Rae & Lonborg, 2015; Yuen et al., 2018) and solely general metrics of social media use (i.e., frequency, duration), we have incorporated more detailed data regarding emerging adults' social media use in our analyses, such as platform, activity of use, and social ties. Our contribution furthermore consists of the combined use of objective data and subjective self-report data regarding young adults' social media use. This is possible through the fusion of passively sensed phone data and subjective ecological momentary assessments gathered over seven days, five times a day. While subjective self-report provides researchers with young people's lived, personal experiences, objective data is valuable because it provides insight into the accuracy of young people's recollections and therefore adds reliability. By using intensive longitudinal data and multi-level modelling, we were able to tease apart between-person from within-person effects. The current study, including research questions, hypotheses, and analyses, was preregistered on the Open Science Framework (https://osf.io/ezuy8/).

In this study, we first aimed to replicate the recent findings of Beyens and colleagues (2020) and expected to find heterogeneity in emerging adults' relationship between their affective wellbeing and their social media use. While Beyens and colleagues have worked to provide detailed individual effect sizes, the field continues to develop rapidly and a recent critique of this approach (Vuorre et al., 2022) has led us to take a step back and limit ourselves here to reporting on the absence or presence of heterogeneity rather than specific individual effects. Second, we aimed to contribute to a better understanding of in which cases young people differ in how social media use influences their affective wellbeing. We did this by investigating whether dominant platform (i.e., which platform is used the most), activity/passivity of social media use (i.e., how active one is on social media during use), and social ties (i.e., whether one has mostly seen posts from/interacted with close or distant social ties) played a predictive role in individuals' relationship between social media use and affective wellbeing.

Regarding social media activity, we hypothesised that predominantly passive use would be related to negative effects of social media use on affective wellbeing (and conversely, predominantly active use will be related to positive effects on affective wellbeing), but only for a subset of individuals as found by Beyens and colleagues (2020). Furthermore, we expected that predominant contact (operationalised as either seeing or interacting) with close social ties on social media would be linked to more positive associations between social media use and affective wellbeing than contact with mostly distant social ties. However, since little comparative work has been done on social media platforms and their relationships to emerging adults' affective wellbeing, we have no pre-specified hypothesis for most-used social media platforms.

We also investigated whether trait-level psychological characteristics such as fear of missing out, rejection sensitivity, and self-compassion played a moderating role in individuals' relationship between social media use specifics and prospective affective wellbeing. Based on our discussion of the included moderator variables above, we hypothesized the following moderating effects. First, we hypothesized that young adults with higher levels of FoMo would be more likely to exhibit negative effects of social media use on their wellbeing. Similarly, we expected to see that for individuals scoring high on rejection sensitivity, the association between social media use (which we expected to be mostly passive) and affective wellbeing would be negative. Finally, we hypothesized that the higher young adults scored on self-compassion, the more likely it was that they would exhibit a positive effect or no significant effect of social media use on affective wellbeing.

Method

Participants

The study presented here is part of a larger project examining the relationship between young women's digital media use and wellbeing. Participants were recruited through the university's online participant recruitment system as well as through social media. Because the larger project was focused on testing an app which was specifically developed for a female audience, participants were considered eligible for participation if they self-identified as female or gender invariant/non-conforming, were between 18 and 31 years of age, used an Android-operated smartphone (due to iOS devices not allowing for app tracking), and were shown to score between "Mild" to "Moderate" on depression, anxiety or stress symptoms at screening. Participants reporting "Severe" or "Extremely Severe" levels of depression, anxiety or stress symptoms at screening were excluded from the study, and were informed of their mental health status and referred to the university psychologist, general practitioner, or their social network for help.

A total of 607 people filled out the screening. Out of those 607, 178 young adults were eligible to participate (i.e., they met the inclusion criteria), and out of those 178, 139 young adults were willing and able to participate in the study (M_{age} = 21.11, $SD_{age.}$ = 3.24, range = 18–31). These 139 eligible participants were tested between July 2020 and March 2021. Although 139 participants were tested, a number of participants were excluded from analyses for analytical reasons (see "Assumption checks" *section. Data cleaning*). As a result, 117 participants were included in the multilevel analyses outlined below. For the sample's demographic information, see Table 1.

Procedure

While the general design of the larger project is outlined here for the purpose of transparency and overview, we only included details regarding elements that pertain to the specific study presented here (as preregistered on OSF; see "Transparency and openness" section).

After having been selected for participation following initial screening, eligible participants were provided additional information regarding the study, and—if interested—were sent an online consent form and link to the pre-test questionnaires. During the pre-test session, participants filled in a range of demographic and psychological questionnaires. Upon completion of the pre-test session, participants were sent instructions on how to install the Effortless Assessment of Risk States (E.A.R.S.; Lind et al., 2018) software app on their smartphone. Through the E.A.R.S. app, their social media app use was passively monitored, and ecological momentary assessment (EMA) prompts were sent during the EMA phase.

Table 1 Participant characteristics and descriptives

Characteristic	*n*	%	Mean (SD)	Median [Min, Max]
Gender			n/a	n/a
Female	115	98.3		
Gender invariant/non-conforming	2	1.7		
Age			20.8 (2.98)	20 [18, 31]
18–20	68	58.1		
21–23	27	23.1		
24–26	16	13.7		
27–31	6	5.1		
Country of birth			n/a	n/a
Netherlands	72	61.5		
Other European countries: (Belgium, Bulgaria, Croatia, Cyprus, Germany, Italy, Latvia, Lithuania, Portugal)	37	31.6		
Other non-European countries: (Curaçao, India, Iran, Mexico, Ukraine, United States)	8	6.9		

During the 7-day EMA phase that followed the pre-test session, participants received assessment prompts five times a day between 9am and 11pm on weekdays, and between 10am and midnight on weekend days. In each of the momentary assessments, participants were asked to answer nine questions regarding their momentary affective state (e.g., “How happy do you feel right now?”, adapted from Van Roekel et al. (2014)). In addition, participants were asked to indicate a) whether they had spent time on social media in the last 30 minutes and how they would evaluate their social media use if they had, b) which categories of people (i.e., close or distant social ties) they had seen content of or been in touch with on social media and in what proportion, and c) what sort of activity they had engaged in (i.e., active or passive) on social media and in what proportion. During this phase, objective social media use data was collected passively (i.e., in the background) by the E.A.R.S. tool, including time stamps of use and app name. A time window of 30 minutes prior to the EMA assessment was chosen to minimize participants’ recall bias, which has been shown to occur in social media studies (Verbeij et al., 2021).

Following the EMA phase, participants were sent instructions on how to delete the E.A.R.S. app from their smartphone and were asked to fill in a range of post-test questionnaires. After having completed their participation in the study, participants were given their choice of compensation. For participation in the study, participants were compensated with €20 or 3 study participation credits, depending on their preference. This study was approved by the university’s Faculty of Social Sciences Ethics Committee (approval nr. ECSW-2019–162).

Measures

An overview of the measures can be found in Table 2.

Positive affect

At each EMA assessment, four questions were asked to measure positive affect (“How *happy/relaxed/energised/satisfied* do you feel right now?”). In order to include both low arousal positive affect (i.e., relaxed, satisfied) as well as high arousal positive affect (i.e., happy, energised) (Van Roekel et al., 2014), participants were asked to answer these questions on a 7-point Likert scale (1 = “Not at all, 7 = “Extremely”). Positive affect scores were generated for each assessment by averaging participants’ responses to the four positive affect questions.

General social media use

Duration of use Duration of social media use in the 30 minutes preceding an EMA assessment was measured using passive monitoring data collected by the E.A.R.S. app. Duration of use was expressed in minutes.

Presence of use Due to unforeseen issues with the data collected by E.A.R.S. (see “Assumption checks” *section. Data cleaning*) we included a variable that was not preregistered, namely a binary ‘presence of social media use’ variable. Presence of social media use in the 30 minutes preceding an EMA assessment was measured using an EMA question. For each assessment, participants were asked to indicate whether they had used social media in the 30 minutes preceding the assessment. Responses were coded as a binary variable (0 = no use, 1 = use).

Most-used social media platform

Using data passively collected by the E.A.R.S. app, we established for each assessment which social media platform (if

Table 2 Study Measures Overview

Measure	Frequency	Source	Analytic Role
Positive affect	Every EMA	Self-report	Dependent variable
General social media use			
Presence of use	Every EMA	Self-report	Independent variable
Duration of use*	Every EMA	Passive sensing	Independent variable
Most-used social media platform*	Every EMA	Passive sensing	Independent variable
Proportion of active social media activities*	Every EMA	Passive sensing	Independent variable
Proportion of activities related to close social ties*	Every EMA	Passive sensing	Independent variable
Social media time quality	Every EMA	Self-report	Independent variable
Fear of missing out	Once, at pre-test	Self-report	Moderator
Rejection sensitivity	Once, at pre-test	Self-report	Moderator
Self-compassion	Once, at pre-test	Self-report	Moderator

More information is given about the measures denoted with an asterisk *, see “Data preparation and analyses” section any) had been used the longest in the 30 minutes preceding the assessment. Our selection of main social media platform categories was based on whether or not platforms matched our definition of social media (as discussed earlier). Platforms that appeared in the data but that did not strictly match our definition were assigned to the category Other. After inspection of the data, we assigned Tumblr, Reddit, Pinterest and LinkedIn to the Other category of social media platforms.

Proportion of active social media activities

If participants indicated they used social media in the last 30 minutes, they were asked whether they had spent their time passively ("Exclusively spent time scrolling/reading/watching posts"), actively ("Exclusively spent time sharing/posting/commenting on posts"), or both ("Both of the above, in the following division:"). If participants indicated to have done both, they were presented with a slider to indicate the proportion of time spent passively vs. actively (e.g., 60/40 passively/actively). This percentage of passive use was later recoded into percentage of active use for the purpose of analyses. Values thus ranged from 0 (only passive use) to 100 (only active use).

Proportion of social media activities related to close ties

If participants had indicated to have used social media in the last 30 minutes, they were asked whether they had been in touch with/seen posts from close social ties ("Close contacts (e.g., friends, family, romantic partner)"), distant social ties ("Distant contacts (e.g., acquaintances, pages, companies, celebrities)"), or both ("Both close and distant contacts, in the following division:"). If participants indicated to have done both, they were asked to indicate the percentage of social media encounters related to close social ties (e.g., 60/40 close/distant). Variable values thus range from 0 (only distant contacts) to 100 (only close contacts).

Social media quality

To further explore the circumstances under which social media use may be related to differences in positive affect, we included an additional exploratory variable: participants' subjective rating of the quality of their social media experience. Specifically, participants were asked to indicate how they would evaluate their social media use, if they had used social media use in the 30 minutes prior to the assessment. Participants could choose between "Have not used social media in the last 30 min", "Not good at all", "Not so good", "It was OK", "Good", and "Very good".

Fear of missing out

Fear of missing out (FoMO) was assessed using the Fear of Missing Out Scale (FoMOS; Przybylski et al. (2013)). The FoMOS consists of ten items, which are answered on a 5-point Likert scale (1 = "Not at all true of me", 5 = "Extremely true of me"). Examples of FoMOS items are "I fear others have more rewarding experiences than me", and "I get worried when I found out that friends are having fun without me". The FoMOS was shown to have good internal consistency in the current sample (Cronbach's $\alpha = 0.80$). Individual FoMO scores were determined by averaging over all ten questionnaire items, producing a FoMO score ranging between 1 and 5.

Rejection sensitivity

Rejection sensitivity was determined for each participant using the Rejection Sensitivity Questionnaire for Adults (A-RSQ; Berenson et al. (2009)). The A-RSQ consists of 9 situations which all are comprised of 'A' and 'B' items, which are answered on a 6-point Likert scale (A items: 1 = "Very unconcerned", 6 = "Very concerned"; B items: 1 = "Very unlikely", 6 = "Very likely"). An example situation-items combination is: "You ask your parents or another family member for a loan to help you through a difficult financial time" (situation), with the following statements to be answered: "How concerned or anxious would you be over whether or not your family member would want to help you?" (item 1A) and "I would expect that they would agree to help as much as they can" (item 1B). The A-RSQ was shown to have sufficient internal consistency in the present sample (Cronbach's $\alpha = 0.72$). A rejection sensitivity score was calculated for every participant by computing the following for each situation: the rejection concern (part A of a given situation) * (7 – acceptance expectancy (reverse coding part B of a given situation)). Finally, the average was calculated over the 9 resulting situation rejection sensitivity scores, yielding a potential rejection sensitivity score between 1 and 36.

Self-compassion

Self-compassion was measured at pre-test using the Self-Compassion Scale (SCS; Raes et al. (2011)). The SCS consists of 12 items that assess how compassionate one is towards him- or herself, which are answered on a 5-point Likert scale (1 = Almost never, 5 = Almost always). An example item is "When I fail at something important to me I become consumed by feelings of inadequacy". The SCS was shown to have good internal consistency in the present sample (Cronbach's $\alpha = 0.84$). A self-compassion score was calculated for each participant by averaging (reversed, where applicable) item scores, producing a questionnaire score between 1 and 5.

Data preparation and analyses

All data processing and analysis was done in R Studio. For the complete script and outputs, please see the R Markdown file uploaded on OSF. There are a number of small deviations from our preregistration which have been documented on OSF. For both, see "Transparency and openness" section.

Data cleaning

During the data manipulation necessary to convert E.A.R.S. social media use data to assessment-level data, we discovered a data resolution issue on the side of the E.A.R.S. app. Due to resolution issues of the objective data (i.e., app use window sizes), we were not able to reliably map all the objective data to the ecological momentary assessments. Specifically, in a number of cases, the measuring windows of the app tracking were too large for us to tell whether any app use that had happened within a window had actually taken place in the 30 min prior to the relevant EMA assessment or not. This was the case for 2433 out of 3.294 assessments. We have explored whether the resolution issue was related to participants or social media platforms, but this turned out not to be the case; resolution problems seemed random. This exploration has also been included in the R Markdown file containing this study's scripts and outputs, and can be found on OSF (https://osf.io/2sbtc). A more detailed elaboration of the issue can also be found in the study script. Given this issue, the analyses involving social media duration and most-used platform (which are the analyses that employ E.A.R.S. social media data) could not be considered reliable and should be interpreted with utmost care. A multilevel analysis with a binary social media use variable based on self-report data has been included in the present paper to supplement the social media use duration analysis.

Furthermore, due to E.A.R.S.' programming, the app could continue to send EMA prompts to participants past the EMA phase's end date if participants forgot to (or chose not to) delete the E.A.R.S. app from their phone. As a result, it was possible for participants to have completed more than 35 assessment data points. To ensure that all participants had a similar number of data points, participants' assessment data were trimmed to official start and end days of the EMA phase. Additionally, participants needed to have completed at least a third of the assessments, setting our cut-off point at a 12-assessment minimum. On average, participants completed 26 assessments, leading to an average compliance rate of 74.3%. Participants with fewer than 12 assessments ($n = 14$) were excluded from the dataset. This was done after the start–end-date trimming described above.

Finally, data were checked for within-person variance in the dependent variable (i.e., positive affect). One participant was found to have no variance in positive affect scores and was excluded from the dataset. For the remaining 117 participants, exploratory and confirmatory factor analysis (not preregistered, see the Deviations from Preregistration document on OSF; https://osf.io/2sbtc) was conducted on the positive affect variable to confirm that the separate positive affect variables (i.e., happy, relaxed, energised, and satisfied) did indeed load sufficiently on the latent positive affect variable. This was found to be the case. These analyses can be found in the study's R Markdown file on OSF (see "Transparency and openness" section).

Assumption checks

Assumptions of heterogeneity, linearity and homoscedasticity were checked for each of the multilevel models by means of visual inspection of residual panel plots. Panel plots were generated in R using the *ggResidpanel* package's resid_panel function, and the resulting panel plots can be found in the R Markdown file containing the complete R script and outputs, on OSF (https://osf.io/2sbtc). Assumptions were not violated for any of the models.

Multilevel models

To answer our research questions, we ran six sets of models (4 preregistered, and 2 added post-hoc). Each set contained four models: Model 0 consisted of that set's independent variables (i.e., social media duration, presence of social media use, most-used platform, activity of social media use, proportion of close-tie encounters, and social media quality), and the dependent variable (i.e., positive affect). Models 1 to 3 consisted of the independent variable pertaining to that set, the dependent variable, and one of our moderator variables (i.e., self-compassion, rejection sensitivity, or fear of missing out). Each model furthermore included Assessment (i.e., assessment number) as a covariate to control for trend effects over the course of the assessment phase.

Following a model-building approach, within each of these models (0–4), we ran three models according to the following three steps: a) an intercept-only model (to determine intra-class correlation and thus appropriateness of multilevel modelling), b) a fixed effects and random intercepts model, and c) a fixed effects and random intercepts and slopes model (to determine whether there were between-person differences in within-person associations). Last, we added a different moderator to each model set's final model (model c). Model-building steps were compared with each other for fit indices using Chi-Square tests. All analyses except the model set with presence social media use and social media quality as independent variable have been detailed in the preregistration of this study.

For our multilevel analyses, fear of missing out, rejection sensitivity, and self-compassion scores were group-level mean centred. Additionally, for the social media duration, activity percentage, and close tie percentage variables, trait (i.e., a participant's mean) and state components (i.e., a participant's deviation from their own mean at any given assessment) were computed and used in analyses. For presence of social media use and most-used platform analyses, no trait and state components could be computed since these were dummy variables.

As a result of the review process we have additionally run the analyses reported below using Bayesian statistics as well (in R using the *brms* package; Bürkner, 2017) to confirm that our results were not a simply result of relatively low power. We have indeed confirmed that the Bayesian and frequentist models produce the same patterns of results. The Bayesian analyses and their output can be found in the R Markdown script shared on OSF (https://osf.io/2sbtc).

Transparency and openness

This study's research questions, hypotheses, design, and analyses were preregistered on OSF (https://osf.io/ezuy8/). The R Markdown file containing the complete R script and outputs can likewise be found on OSF (https://osf.io/2sbtc), as can the Deviation from Preregistrations (https://osf.io/vabwj/). All data have been stored at the Radboud Data Repository and can be accessed at https://data.ru.nl/login/reviewer-75239/cfRZPJCBxDnArAVrsL9gumTSMZBfuBZz-DBYpCQqL7o.

Results

Descriptives

Table 3 presents the descriptive statistics of all variables of interest. On average, participants scored moderately on self-compassion (M_{SCS} = 2.82, SD_{SCS} = 0.62), moderately on fear of missing out (M_{FoMOS} = 2.53, SD_{FoMOS} = 0.64), and slightly above average on rejection sensitivity ($M_{A\text{-}RSQ}$ = 9.14, $SD_{A\text{-}RSQ}$ = 3.50) as compared to healthy comparison groups (Berenson et al., 2016, 2009). According to our passively sensed smartphone use data, Instagram (featured in 9% of the assessments) was the most-used platform in the 30 minutes preceding assessments, followed by Snapchat (in the case of 4.6% of the assessments) and TikTok (in the case of 1.8% of the assessments).

Activity on social media was predominantly passive with social media use in the half hour prior to an assessment being rated as entirely passive in 75.3% of all assessments. On average, around half (49.2%, SD = 47.7) of the 30 minutes prior to assessments was allocated to seeing posts of and/or interacting with close social ties. Overall, participants scored moderately on positive affect (M = 3.88, SD = 0.79).

Additionally, correlations between variables of interest and positive affect scores were computed, see Table 4. Between-person correlations with positive affect were calculated using standard group-level computations, whereas a repeated-measures correlation technique was used to compute the common within-individual association of our variables of interest with positive affect (Bakdash & Marusich, 2017).

Multilevel analyses

Due to the data resolution issues described earlier, analysis results for the affected models will not be discussed here due to their unreliability. Instead, these results can be found in our Supplementary Materials.

Presence of social media use and positive affect

The extra, exploratory set of models with presence of social media use as dummy predictor showed that, on average, participants' positive affect was lower if they had reported to have used social media prior to the assessment (B = -1.90, p = 0.001). Furthermore, following the addition of random slopes, model comparison indicated that there was between-person heterogeneity in within-person associations (Chi^2 = 8.124, p = 0.004; Table 5), meaning that there is reason to think the relationship between presence of social media use and positive affect is not the same or necessarily present for all participants, and may in fact be present for some (and be either negative or positive, in that case) and absent for others.

Separate models building upon the fixed + random effects model (model 2.0.c) were subsequently run with the addition of self-compassion (model 2.1), rejection sensitivity (model 2.2), and fear of missing out (model 2.3) as moderator. No moderators were significant (see Table 5).

Activity on social media and positive affect

The model set with the percentage of activity on social media as numeric predictor indicated that, on average, participants' positive affect did not relate to their activity on social media in the 30 min prior to the assessment. Additionally, adding random slopes to the model did not improve fit (Chi^2 = 1.634, p = 0.442), indicating that there were no between-person differences in the within-person association between most-used social media platform and subsequent positive affect. Since no heterogeneity was found, the moderator analyses featuring self-compassion, rejection sensitivity and fear of missing out as moderators were not run. For model statistics, see Supplementary Table 3.

Table 3 Variable descriptives

Characteristic	*n*	%	Mean (SD)	Median [Min, Max]
Self-compassion score	117	100	2.82 (0.62)	2.83 [1.50, 4.58]
FoMo score	"	"	2.53 (0.64)	2.40 [1.20, 3.80]
Rejection sensitivity score	"	"	9.14 (3.50)	8.67 [1.89, 20.0]
Positive affect score	"	"	3.88 (0.79)	3.91 [1.65, 6.07]
Social media variables	3294	100		
Presence of use	"	"	n/a	n/a
Used social media	1663	50.5		
No use of social media	1631	49.5		
Quality of social media use				
Have not used social media	1631	49.5	n/a	n/a
Not good at all	17	0.5		
Not so good	125	3.8		
OK	675	20.5		
Good	642	19.5		
Very good	204	6.2		
Social media activity (percentage)	1663	100	18.4 (35.2)	0 [0, 100]
Active only	197	11.8		
Passive only	1252	75.3		
Both	214	12.9		
Close tie encounters (percentage)	1663	100	49.2 (47.7)	50 [0, 100]
Close ties only	702	42.2		
Distant ties only	759	45.6		
Both	202	12.2		
Duration of use (minutes)*	3294	100	1.83 (4.29)	0 [0, 27.2]
0 min	973	29.5		
More than 0 min	576	17.5		
Unable to establish	1745	53		
Most-used platform*	3294	100	n/a	n/a
Facebook	43	1.3		
Instagram	297	9		
Snapchat	150	4.6		
TikTok	59	1.8		
Twitter	32	1		
Other	25	0.7		
No use of social media	943	28.6		
Unable to establish	1745	53		

For social media variables, the *n* refers to assessments (over all participants). For all other variables, the *n* refers to participants. Presence of social media use based on EMA self-report item, not on E.A.R.S. data

* As established in "Assumption checks" *section. Data cleaning*, our dataset is missing information for a large portion of assessment-level data for these variables and were interpreted with caution

Percentage of close-tie encounters on social media and positive affect

The final models with percentage of encounters with close social ties on social media as numeric predictor showed that, on average, there was no association between percentage of close tie encounters on social media and positive affect. However, following the addition of random slopes, model comparison indicated that there was between-person heterogeneity in within-person associations between close tie encounters and positive affect ($Chi^2 = 6.344$, $p = 0.042$; Table 6), meaning that there is reason to think the relationship between close-tie percentage and positive affect is not the same or necessarily present for all participants. Separate models building upon the fixed + random effects model (5.0.c) were then run with the addition of self-compassion (model 5.1), rejection sensitivity (model 5.2), or fear of missing out (model 5.3) as moderator. No moderators were significant, see Table 6.

Table 4 Between- and within-person correlations of numeric variables with Positive Affect

Independent variable	Between-person (*df, p*)	Within-person (*df, p*)
Age	-0.03 (115, 1.000)	-
Fear of missing out score	-0.14 (115, 1.000)	-
Rejection sensitivity score	-0.35 (115, 0.002) **	-
Self-compassion score	0.37 (115, 0.001) ***	-
Social media duration	0.01 (114, 1.000)	-0.06 (1434, 0.027) *
Percentage of close tie encounters	-0.07 (115, 1.000)	0.07 (1533, 0.007) **
Percentage of active use	0.05 (115, 1.000)	0.07 (1537, 0.003) **
Presence of social media use (dummy)	-	-0.10 (3176, 0.000) ***
Most-used platform (dummy)		
Facebook	-	-0.04 (513, 0.370)
Instagram	-	-0.03 (513, 0.432)
Snapchat	-	0.06 (513, 0.164)
TikTok	-	-0.05 (513, 0.234)
Twitter	-	0.06 (513, 0.189)
Other	-	0.04 (513, 0.337)

No between-person correlations with positive affect have been computed for the dummy variables. For between-person correlation, Holm's correction for multiple comparisons was used using the rcorr.adjust function in R's RcmdirMisc package. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Social media quality and positive affect

After our full set of planned analyses were run and results were gathered, we wanted to explore whether there was a relationship between emerging adults' (self-reported) quality of social media use and their affective wellbeing following that social media use. Thus, we ran a non-preregistered model with self-reported social media use quality use as predictor and positive affect as dependent variable. Our models showed that there was a group-level effect for quality of social media use. Specifically, the positive social media quality categories (i.e., 'good' and 'very good') were not significantly related to positive affect, while the negative categories 'not good at all' (B = -0.926, p = 0.02) and 'not so good' (B = -0.89, $p<0.001$) quality were both negatively related to positive affect. Additionally, the category that was intended to be neutral (i.e., the 'it was ok' social media quality category) was also found to be negatively related to positive affect (B = -0.40, $p<0.001$). Full model statistics can be found in Supplementary Table 4. Furthermore, we found no between-person heterogeneity in this association, as the addition of random slopes to this model did not prove to be a better fit ($Chi2 = 1.771$, p = 0.183). In the absence of heterogeneity, moderator models were not run.

Discussion

In this study, we investigated the relationships between both general as well as specific social media use variables, psychological characteristics, and emerging adults' momentary positive affect after social media use. An important contribution of this study was the combined use of subjective and objective data. Unfortunately, we discovered during data exploration that the objective social media use data that was collected through the E.A.R.S. tool (Lind et al., 2018) was too low in resolution to yield reliable results (see "Assumption checks" section). This problem pertained specifically to the analyses involving social media use duration and most-used platform as predictor variables, since that information was to be extracted via passive phone sensing. As a result, the outcomes of those analyses (i.e., that there is no relationship between social media duration or platform and positive affect) cannot be considered reliable, since there is a possibility that information was missing in our analyses as a result of the low data resolution.

In line with our preregistered expectations and previous work (Beyens et al., 2020), we found heterogeneity in the relationship between presence of social media use and positive affect. Furthermore, following recent research suggesting that the 'passive use hypothesis' does not hold for all young people (Valkenburg et al., 2021), we hypothesised that we too would find there to be heterogeneity in the relationship between activity of social media use and affective wellbeing. Our data however did not confirm this expectation, as we did not find a group-level effect of social media activity on affective wellbeing, nor potential heterogeneity. This may have been for several reasons. First, our descriptive statistics showed that active use of social media was in fact very rare (see Table 3). It is thus possible that differences between levels of activity could be found had more data been present on the active side of the spectrum. The fact that

Table 5 Model statistics for Presence of social media use and Positive affect

Model Set 2 Presence of social media use	Model 2.0 – No moderators								Model 2.1 –Self-compassion				Model 2.2 –Rejection Sensitivity				Model 2.3 –FoMo			
	2.0.b Fixed effects				2.0.c Random slopes				2.1 Fixed + random slopes				2.2 Fixed + random slopes				2.3 Fixed + random slopes			
	B	*SE*	*P*	*b*	*B*	*SE*	*p*	*b*	*B*	*SE*	*P*	*b*	*B*	*SE*	*p*	*b*	*B*	*SE*	*p*	*b*
Fixed part																				
Intercept	**3.95**	**0.08**	**0.000**	**-0.02**	**3.95**	**0.08**	**0.000**	**-0.02**	**3.95**	**0.07**	**0.000**	**0.05**	**3.95**	**0.07**	**0.000**	**0.05**	**3.95**	**0.07**	**0.000**	**0.05**
Assessment	0.00	0.00	0.438	-0.01	0.00	0.00	0.484	0.00	0.00	0.00	0.432	0.01	0.00	0.00	0.441	0.01	0.00	0.00	0.474	0.01
Presence of use	**-0.19**	**0.03**	**0.000**	**-0.08**	**-0.18**	**0.04**	**0.000**	**-0.08**	**-0.18**	**0.04**	**0.000**	**-0.15**	**-0.18**	**0.04**	**0.000**	**-0.15**	**-0.18**	**0.04**	**0.000**	**-0.15**
Presence of use * moderator									0.01	0.06	0.879	0.00	0.00	0.01	0.795	0.00	0.06	0.06	0.369	0.03
Random part																				
σ^2 residual (SD)	0.59 (0.89)				0.78 (0.88)				0.77 (0.88)				0.77 (0.88)				0.77 (0.88)			
σ^2 between-person (SD)	0.79 (0.76)				0.57 (0.76)				0.49 (0.70)				0.49 (0.70)				0.56 (0.75)			
σ^2 presence of use (SD)					0.03 (0.16)				0.02 (0.16)				0.02 (0.16)				0.02 (0.16)			
Model fit																				
Deviance	8915.4				8907.3				8889.4				8891.2				8904.1			
AIC	8925.4				8919.3				8905.4				8907.3				8920.1			
BIC	8955.9				8955.9				8954.2				8956.1				8968.9			
Chi^2 (df)					**8.124 (2)**		**0.004**		**17.836 (2)**		**0.000**		**15.988 (2)**	**0.000**			3.19 (2)		0.203	

Number of participants in analyses: 117, number of assessments in analyses: 3294

Bold values indicate parameters that belong to significant *p*-values

Table 6 Model statistics for Percentage of close tie encounters and Positive affect

Model Set 2 Percentage close tie encounters	Model 2.0 – No moderators								Model 2.1 –Self-compassion				Model 2.2 –Rejection Sensitivity				Model 2.3 –FoMo			
	2.0.b Fixed effects				2.0.c Random slopes				2.1 Fixed + random slopes				2.2 Fixed + random slopes				2.3 Fixed + random slopes			
	B	*SE*	*P*	*b*	*B*	*SE*	*p*	*b*	*B*	*SE*	*P*	*b*	*B*	*SE*	*p*	*b*	*B*	*SE*	*p*	*b*
Fixed part																				
Intercept	**3.77**	**0.08**	**0.000**	**-0.00**	**3.77**	**0.08**	**0.000**	**-0.00**	**3.77**	**0.08**	**0.000**	**-0.02**	**3.77**	**0.08**	**0.000**	**-0.02**	**3.77**	**0.08**	**0.000**	**-0.02**
Assessment	0.00	0.00	0.509	0.01	0.00	0.00	0.503	0.01	0.00	0.00	0.391	0.02	0.00	0.00	0.460	0.02	0.00	0.00	0.507	0.02
Close tie % (trait)	-0.00	0.00	0.953	-0.00	-0.00	0.00	0.954	-0.00	-0.00	0.00	0.709	-0.02	-0.00	0.00	0.875	-0.01	0.00	0.00	0.996	-0.00
Close tie % (state)	**0.06**	**0.02**	**0.004**	**0.06**	**0.06**	**0.02**	**0.016**	**0.06**	**0.06**	**0.02**	**0.010**	**0.06**	**0.06**	**0.02**	**0.010**	**0.06**	**0.06**	**0.02**	**0.017**	**0.06**
Close tie % (trait) * mod									-0.00	0.00	0.545	-0.04	-0.00	0.00	0.283	-0.07	0.00	0.00	0.800	0.02
Close tie % (state) * mod									-0.01	0.04	0.741	-0.00	0.00	0.00	0.443	0.02	0.00	0.04	0.826	0.00
Random part																				
σ^2 residual (SD)	0.72 (0.85)				0.71 (0.84)				0.71 (0.84)				0.70 (0.84)				0.70 (0.84)			
σ^2 between-person (SD)	0.57 (0.76)				0.57 (0.76)				0.49 (0.70)				0.49 (0.70)				0.56 (0.75)			
σ^2 Close tie % (state) (SD)					0.01 (0.76)				0.01 (0.11)				0.01 (0.12)				0.01 (0.12)			
Model fit																				
Deviance	4437.2				4430.9				4409.5				4410.5				4427.9			
AIC	4451.2				4448.9				4435.5				4436.5				4453.9			
BIC	4489.1				4497.6				4505.8				4506.9				4524.2			
Chi^2 (df)					**6.344 (2)**		**0.042**		**21.386 (4)**		**0.000**		**20.357 (4)**	**0.000**			3.014 (4)		0.555	

Number of participants in analyses: 117, number of assessments in analyses: 1655

Bold values indicate parameters that belong to significant *p*-values most emerging adults are predominantly passive consumers of social media content is well-known (e.g., Escobar-Viera et al., 2018; Griffioen et al., 2021). Future studies may be required to observe emerging adults for longer periods of time in order to gather sufficient quantities of passive use data. We would not recommend assigning participants to active social media tasks in order to gather sufficient data on active use, as active use in such scenarios may be of a different (non-naturalistic) quality and distort findings. A second potential explanation for not finding a relationship between activity of use and positive affect could be that there may be a dose-response effect of activity/passivity. Specifically, mostly using social media passively may only start to matter in larger quantities. A recent study by Beyens and colleagues indeed suggests that this may be the case, having found a dose-response effect of actively using social media on wellbeing (2020).

Moving on to close versus distant social ties on social media, we found—as expected—a group-level relationship between a higher percentage of close-tie encounters on social media and higher positive affect. Additionally, our results indicated between-person heterogeneity in this relationship, which mean that there are likely emerging adults who exhibit this relationship (and for whom it may be either negative or positive) and emerging adults who do not display this relationship.

To supplement our exploration of emerging adults' social media use, we decided to include an additional analysis: a model involving self-reported quality of social media use as predictor. Rather than the importance of what you do and who you encounter per se, it may be the case that how social media use affects affective wellbeing depends most on how emerging adults interpret and process their time on social media. The results of our additional analysis suggest evaluating time on social media as being a neutral or a bad/negative experience is related to subsequent lower levels of positive affect. The finding that even a neutral evaluation is associated with lower positive affect is curious. It might reflect a tendency to downplay negative emotions (i.e., not wanting to admit it was not very nice or fun), or it could suggest that emerging adults are used to feeling just a little worse after social media which may lead them to evaluate the social media session itself as neutral because it was not out of the ordinary for them. These speculations, however, are just that, and require detailed future research to determine what may in reality be the cause of this finding.

Last, contrary to our expectations, we found no moderating effects of psychological characteristics (i.e., self-compassion, rejection sensitivity, and FoMo) in any of the investigated associations. Exploration of the descriptives indicated that spread of scores on self-compassion, rejection sensitivity and FoMO was reasonable, suggesting that a lack of variance is unlikely to play a role in the absence of moderation effects. What may have played a role, however, is the stability of the moderating variables we have investigated in the present study. It is possible that social media (and media effects in general) are more fleeting and dynamic, and may therefore depend more on in-the-moment factors than stable variables like one's fear of rejection.

Further methodological considerations for future research

While the study presented here has provided insight into the intricacies of associations between emerging adults' social media use and their positive affect, several methodological considerations should be kept in mind. First, although ecological momentary assessment data offer more detailed information as well as minimization of recall biases, the dependency between variables measured in the same assessment can be problematic. For instance, both quality of use and positive affect were measured in the same momentary assessments. Therefore, finding a strong relationship between 'how one feels' and 'how one feels about their time on social media' is not necessarily surprising; if a participant just indicated that they felt relatively low on positive affect in general, this could have directly affected how they subsequently answered a question regarding social media quality. This holds true for all variables that are measured within the same limited span of time and using the same assessment method. Disentangling spill-over effects from true associations will be important in future studies and may be achieved by using different measurement moments and/or sources to collect separate variables (Mestdagh & Dejonckheere, 2021).

Second, objective data is valuable and necessary when it comes to technology use research. We know from earlier work that recall bias is strong when trying to remember social media use (Boase & Ling, 2013; Ellis et al., 2019; Verbeij et al., 2021), which is why social media research can benefit greatly from incorporating objective data. However, as we have seen, extra care is required to ensure that the objective data that is collected is reliable and usable. Such foresight will require researchers to determine in advance (and in great detail) what their different data types will look like and determine whether and how they can be mapped on to each other. Concretely, this calls for building and trying out analysis scripts before data collection has even started. Nevertheless, the use of objective social media use data (in addition to relevant subjective experience data) remains of paramount importance for future social media use effects research, and is well worth the effort; not only to be able to say that there is a discrepancy between subjective and objective reports, or to have reliable data to use in analyses, but also to help emerging adults remember and report on their experiences more accurately.

Third, our results have confirmed the importance of being able to detect between-person differences in relationships between variables. For both analyses where heterogeneity was found (i.e., presence of social media use and percentage of close ties), if we had examined fixed-effects models exclusively, our conclusions would have been different. We would have have assumed that this effect holds for every participant.

Last, it is important to note that our sample consisted exclusively of female emerging adults with mild to moderate depression, anxiety or stress symptoms as measured through the DASS-21. The homogeneous nature of this sample may have limited our ability to find heterogeneity in some of our models. Additionally, our conclusions can not be straightforwardly extended beyond the population sampled in our study. However, there have been a number of studies suggesting that social media use may affect female users more than male users (e.g., Orben et al., 2019; Abi-Jaoude et al., 2020; The Hill, n.d.). perhaps because women are more attuned to social comparisons based on curated timelines (Choukas-Bradley et al., 2018; Fardouly et al., 2015). Additionally, an increasing number of young people has reported mental health problems (depression, anxiety, and stress being among the biggest issues) in recent years (Centraal Bureau voor Statistiek, 2022). Thus, while our sample does indeed not reflect emerging adults as a whole, it does reflect a part of the emerging adult population that is relevant and to some extent becoming even more relevant in light of increasing mental health issues. That being said, given the resolution that can be achieved with multilevel data and analyses, it would be beneficial to our understanding of social media use effects to work towards more gender-balanced samples. Just as there are great differences between young women, there may similarly be heterogeneity present among young men.

Conclusion

Despite the challenges posed by the quality of objective data in the present study, our results support the claim that the relation between social media use and positive affect is not the same for everyone. While the psychological characteristics examined in this study did not seem to moderate social media use relationships with positive affect, it remains possible that such associations can be found in a sample without depression, anxiety and/or stress symptoms. Alternatively, other—more dynamic—factors may play a moderating role in the association between social media use and affective wellbeing. Finally, the results of our additional exploratory analysis investigating self-reported quality of social media time open the door for a slightly different approach to studying social media use, one focused on emerging adults' personal experience and reflections on their own social media use.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12144-022-04035-5.

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Data availability The datasets generated during and/or analysed during the current study are available in the Radboud Data Repository repository, https://data.ru.nl/login/reviewer-75239/cfRZPJCBxDnArAVrsL9gumTSMZBfuBZz-DBYpCQqL7o.

Declarations

Conflicts of interest No conflicts of interests to declare.

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